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Spring 4-12-2016

SOCIAL MEDIA: A SOURCE FOR UNCOVERING THE DETERMINANTS OF CUSTOMER SATISFACTION IN THE MOBILE SERVICES INDUSTRY (30)

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Abstract

Customer satisfaction is a major concern for most mobile network operators due to the increasing competition in the mobile services industry. As a result, companies have chosen to exploit data as a means to better understand customer needs. Qualitative and Quantitative methods have been employed to understand customer satisfaction in the mobile services sector. However, the efficiency of these methods is arguable due to the increasing competition in the mobile services sector. This study proposes a novel approach to addressing customer satisfaction in the mobile services industry. The design science research paradigm is applied as an overarching design methodology with the application of the SoMeDoA framework to uncover the determinants of customer satisfaction in the mobile services industry. The effectiveness of applying the SoMeDoA framework to uncovering customer satisfaction determinants is validated with a number of interviews as a means to fulfil the steps of Design Science Research. Dataset for this study is captured from Twitter. Tweets about the five major mobile services companies in the UK are extracted for a given time period and analysed. Data analysis is able to show the most crucial determinants of customer satisfaction. In addition, more interesting insights are uncovered during the analysis and evaluation of this study.

Keywords: Customer satisfaction determinants (CSDs), Social Media, Twitter, Social Media Domain Analysis (SoMeDoA), Design Science Research (DSR).

1.0 Introduction

Customer satisfaction is essential for the growth of businesses across various domains. The marketing literature advocates that the ability to quickly respond to customer demands impacts on the long-term success of a company (Narver and Slater 1990, and Webster 1992). Customer satisfaction can drive success for businesses by providing a competitive advantage, increasing market share and profitability (Fornell, 1992-update), and reduce the cost of seeking new customers (Gerpott and Ahmadi, 2015; Vafeiadis et al., 2015).

The primary focus of this study is to identify the elements that drive customer satisfaction in the mobile services sector using data gathered from social media. Social media has become a critical part of the eco-system due to its increasing awareness and usage. Consequently, the knowledge derived from harnessing social media data is able to provide more insights on customers' feelings towards their service provider. In addition, this knowledge can also provide insights for decision-making and in turn increase the profitability. The use of social media for decision-making is popular across various domains and industries. Politicians and political parties use social media as a medium to gauge public opinion on policies and political positions as well as to build public support for candidates running for public offices (Stieglitz and Dang-Xuan 2012). Public health officials use social media as a means to announce seasonal disease outbreaks (such as flu) (Mollema et al., 2015) and advice on precautionary measures to be taken against such diseases. For profit businesses' are tapping into social media resources as a rich source of information and as a business-execution platform for product design and innovation, consumer and stakeholder relations management and marketing (Fulgoni, 2015).

A number of studies have addressed customer satisfaction in the mobile services sector using traditional approaches, such as questionnaires and interviews (Hanif et al., 2010, Bamfo, 2009). However, the effectiveness of these approaches is questionable. This paper seeks to apply a novel framework for understanding the drivers of customer satisfaction in the mobile services industry. We apply the SoMeDoA framework with the DSR methodology to uncover CSDs in the mobile services industry. The next section provides a review of the domain under study.

2.0 Background and Literature Review

Customer satisfaction is regarded as the central element in maintaining long-term customer relationship in the literature of relationship marketing (Siu et al., 2013). Therefore, when customers experience a bad service, it is crucial for companies to re-establish satisfaction as a means to retain unsatisfied customers. Researchers have explored customer satisfaction in various fields and have come up with various definitions for customer satisfaction. A widely used definition in the literature is that of Kotler (2009) who defined customer satisfaction as a person's feeling of pleasure or displeasure resulting from capturing a product's perceived performance (or outcome) in relation to his or her expectations. Another popular definition by Kotler (1994) is 'the key to customer retention is customer satisfaction'. A number of studies have investigated customer satisfaction in various industries. Hanif et al. (2010) investigated the factors affecting customer satisfaction in the telecommunications sector in Pakistan using price fairness and customer services as predicting variables. They found that both variables are not only independently important for satisfying customers but they also complement each other. Bamfo (2009) reports that factors such as; friendly, courteous, knowledgeable and helpful employees, accuracy of bills, competitive pricing, and service quality enhance customer satisfaction. Rahman et al. (2011) found that price plays an important role in the choice criteria for mobile telephone operators in Malaysia. A number of researchers also reported that satisfied customers tend to increase their usage, be brand loyal and convey positive word of mouth (Santouridis and Trivellas, 2010; Lee, 2013; Choi et al., 2008). These will potentially enhance sales and bring about more profit (Oliver, 2010). Leelakulthanit and Hongcharu (2011) investigated the determinants of customer satisfaction by interviewing 400 mobile phone users in Thailand. They found that promotional value, quality of customer service at shops and corporate image play the most important role in determining customer satisfaction. Mobile service providers have to monitor the market continuously to ensure that their offers, charges, signal coverage, and quality of services are better than their competitors' (Almossawi, 2012). Das Gupta and Sharma (2009) reported that in order to retain customers and attract new customers; mobile service providers must provide services with reasonable quality without any hidden price, as these are the two most important determinants of customer satisfaction. Despite the cost and difficulty in measuring customer satisfaction, it is still considered an important method of securing a competitive advantage (Mittal et al., 2005). Consequently, organisations need to seek the determinants of customer satisfaction and provide them to gain a competitive edge in their respective industry. Majority of the above cited studies investigated customer satisfaction with traditional data collection methods such as interviews and questionnaires. However, the area of customer satisfaction is increasingly gaining more audience and researchers are seeking alternative approaches to investigating customer satisfaction.

Agnihotri et al. (2015) investigated the impact of social media on influencing customer satisfaction in Business-to-Business (B2B) sales. They found that social media use has an influence on customer satisfaction and customers value interaction with companies on social media. In addition, they found a positive relationship between responsiveness and customer satisfaction, implying that customers also value timely responses from companies. The use of social media by companies is gradually increasing. As a result, social media is becoming an integral part of companies' success. Social media provides the opportunity for companies to gain more exposure, increase traffic and gain more insights in the marketplace (Stelzner, 2011). From a sales force perspective, social media allows sales people to engage customers and develop social grounds where companies can encourage customers to interact and establish relationships with their customers (Agnihotri et al., 2012). Social media offers platforms where companies can communicate with customers enabling better sales person responsiveness. The extensive use of social media platforms by companies, with increased interaction with customers is causing buyers to gain equal power with sellers in the market place (Prahalad and Ramaswamy, 2004). As a result, customers have a higher expectation from sellers and sellers are at risk of losing their customer base if a concerted effort is not made to satisfy customers (Agnihotri et al., 2015). The next section presents an overview of DSR and the SoMeDoA framework.

3.0 Overview of DSR Methodology and the SoMeDoA Framework

Design science research is a multidisciplinary approach that primarily uses design as a research method or technique to solve a problem and learn from the process of solving that problem (Vaishnavi and Kuechler, 2015). Apart from its popular adoption in information systems, it is also widely used in disciplines such as education, engineering computer science, and health-care. March and Smith (1995) described design science research as the beginning of a new research era that has enabled research to achieve more attention and improved effectiveness by strategically combining research output (product) and research processing (activities) from both natural and design science in a two-dimensional framework. The design science output or artefacts include constructs, models, methods and instantiations while the natural science activities include build, evaluate, theorize and justify (March and Smith 1995). The process of the two-dimensional framework can be described as applying the natural science activities to produce the design science outputs or artefacts; constructs, models, methods and instantiations. Design science achieves the most satisfactory results to a design problem by process of iterative knowledge refinement.

The design research output classification defined by March and Smith (1995) can help establish appropriate measures to build, evaluate, theorize and justify a design science research. The four research outputs are briefly described below:

Constructs: Constructs are a set of concepts that are used to describe problems within a domain and specify their solutions. Constructs also form the vocabulary of a discipline.

Models: Models are a set of statements that express relationships among constructs and represent real-world design activities in a domain (March and Smith, 1995). Models can also be used to suggest solutions to problems in a problem space.

Methods: Methods are a sequence of steps used to execute a task. These steps provide guidelines on how to solve problems using constructs and models. In addition, methods can be described as a set of methodological tools that are created by design science and applied by natural science (March and Smith, 1995).

Instantiations: Instantiations are the utilisation of constructs, models and methods to showcase an artefact in a domain. They demonstrate the effectiveness of the constructs, models and methods (March and Smith, 1995). Newell et al. (1972) describe the importance of instantiations in computer science by explaining how they offer a better understanding of a problem domain and consequently, provide better solutions. Instantiations provide working artefacts that can drive significant advancement improvement in both design and natural sciences. A DSR methodology incorporates five step-wise phases of a design cycle to effectively address a design science research problem. These phases are designed such that knowledge gained from one stage is transferred to the next stage until a desired result is achieved. The DSR phases are awareness of problem, suggestion, development, evaluation and conclusion (Vaishnavi and Kuechler (2015). These phases along with their outputs are described below.

Awareness of Problem: The DSR process begins by identifying the problem under study. The identified problem may arise from multiple sources such as the literature and new developments in the industry. The research problem needs to be clearly defined and articulated. The output of this phase is a formal or informal proposal for new research.

Suggestion: This phase is explored when a research proposal has been presented. Possible solutions about the research problem are explored and evaluated thereby, leading to the acquisition of further insights to the domain under study. The specifications of the appropriate solutions to the research problem are defined. The output of this phase is a conditional design or representation of proposed solutions.

Development: This phase involves further developing and implementing the DSR artefacts based on the suggestions from the previous phases. The outputs of this phase are the artefacts, which are core elements of the DSR process.

Evaluation: The developed artefacts are analysed and evaluated according to the criteria set in the awareness of problem phase. Deviations and expectations should be noted and explained in this phase. If the outcomes derived from the development or evaluation phase do not meet the objectives of the problem, the design cycle returns to the first phase along with the knowledge gained from the process of the first round of work. These phases may be iterated until the artefact evaluation satisfies solution requirements. The outputs of this phase are performance management that should improve the efficiency and effectiveness of the artefact.

Conclusion: This is the last phase of the DSR cycle. The results of the research are written up and communicated to a wider audience in forms of professional publications and scholarly publications (Peffers et al., 2007). Vaishnavi and Kuechler (2015) categorised the knowledge gained in this phase as either firm or loose ends. Firm knowledge are 'facts that have been learned and can be repeatedly applied or behaviour that can be repeatedly invoked', while loose ends are 'anomalous behaviour that defies explanation and may well serve as the subject of further research' (Vaishnavi and Kuechler, 2015). Figure 1 provides a graphic representation of the DSR phases.

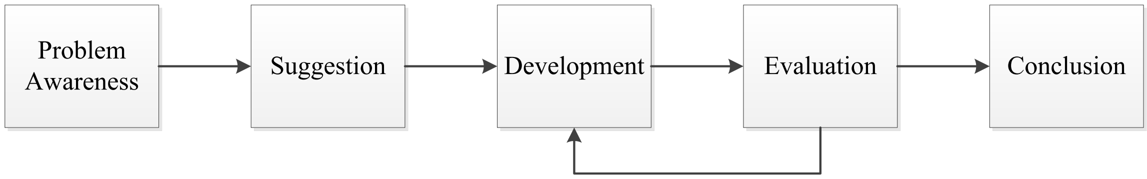

Figure 1. DSR phases

3.1 Overview and Application of the SoMeDoA Framework

The SoMeDoA framework developed by Shirzad and Bell (2013) involves capturing and analysing core elements of social media data. The SoMeDoA framework works by extracting data from specific social media websites (such as twitter) using domain specific search terms that target selected organisations temporal data sets. The generated data can be further analysed using visualisation and analytical tools such as Qlik and Tableau. The SoMeDoA framework consists of four phases namely, data selection, data gathering, temporal separation and temporal coding (Shirzad and Bell 2013). In addition, the SoMeDoA framework works by effectively detecting real-time activities of organisations within a domain. The names of selected organisations are used as query terms to capture tweets about organisations of interest.

An application (Tweetcatcher2), developed on the MATCH project at Brunel University is used to capture tweets and related data such as published date, user ID, tweets, number of following, number of followers, time zone, number of user tweets, re-tweet count, expanded links and sentimental analysis. Sentiment analysis assigns positive, neutral and negative scores to each distinct entity in a text (Pak and Paroubek 2010). The temporal separation and coding analysis are developed for handling Twitter message streams that also categorise tweets based on the number of tweets published and the frequency of occurrences in the selected time slots. Microsoft 2010 is used to carry out the temporal separation of the dataset, which enables tweets to be visualised based on the time and number of tweets generated.

Temporal coding utilises the Grounded Theory Method (GTM) coding approach. GTM is the practice of generating a theory from data (Glaser and Strauss, 1967). Once data is collected, a thematic coding process is used. The coding process supports building conceptualisations and the comparison between elements derived from the coding process help in identifying patterns and relationships between constructs as well as strengthen and support the final model (Strauss and Corbin, 1998). This process is summarized by Strauss and Corbin, (1998, p21) as “Theorising as work that entails not only conceiving or intuiting ideas (concepts) but also formulating them with a logical, systematic, and explanatory scheme”. Nvivo10 is used for organizing, categorizing and searching textual, recorded data. Nvivo10 is selected because it was found to be comprehensive in its functionality, stable in its operation, easy to use, error free, and its large number of standard reports and export facilities. Nvivo10 also proved to be appropriate for manipulating and analysing the dataset gathered for this study. The grounded theory analysis in this study is based on the open coding approach (Corbin and Strauss, 1990)- ‘the process of breaking down, examining, comparing, conceptualising, and categorising data’ (p. 61). The coding process starts with the interpretation of each user’s tweet, followed by drawing together categories and sub-categories into a hierarchy, and the process of integrating and refining categories in order to arrive at a theory. The analysis classifies textual material (i.e. tweets) semantically and provides more relevant and manageable data (Wand and Weber 2002). The process for content analysis are as follows: 1) Storage and categorizing datasets, 2) conducting searches for further analysis in order to generate reports on frequency of words and associated categorisation, 3) creation of categories through computer assisted coding, 4) ontological view by using Protégé Onto-graph (Shirzad and Bell, 2013). Table 1 presents a tabular description of the SoMeDoA framework. The description and the resulting output of each phase is outlined. The next section presents the analysis and results of applying the SoMeDoA framework to this research along with the DSR guidelines.

Phase	Description	Resulting Output
Data Selection	Social media websites are selected as suitable sources for the domain of study	List of social media platforms and associated search terms.

Data Gathering	Data gathering tools are selected and run against the selected Social Media sites.	List of software tools.
Temporal Separation	Public information, news and communications are extracted in order to determine the public activities of organisations (with associated timelines)	DateTime lists files for each organisation.
Temporal Coding	Further analysis of temporal data to uncover topics of importance (with timeline)	Keywords lists and domain ontology. DateTime datalists for each keyword, list or category.

Table 1. The SoMeDoA Research Framework (Bell and Shirzad, 2013)

4.0 Analysis and Results

4.1 Dataset Description

Twitter is selected to carry out this study in order to efficiently detect customers' real time activities within the chosen domain. Twitter users are able to post tweets of up to 140 characters. As a result, users can express their feelings about products and services in a short text. The first part of this research begins by identifying the leading companies in the domain of interest. Data about the companies of interest were obtained by using their Twitter IDs as search/query terms (e.g. '@Vodafone OR #Vodafone, OR Vodafone'). Tweets about the following companies were captured: Vodafone, Virgin, Three, T-Mobile and O2. Tweetcatcher2 was used to gather tweets and related data such as published date, user, number of followers, re-tweet count and sentiment analysis. Tweets were captured from the 27th of June 2015 to the 3rd of July 2015.

4.2 Twitter Temporal Separation

Temporal analysis deals with time components (Lauw et al., 2005). In order to discover if there were changes in customers' feelings towards their mobile provider over time, tweets were categorised as they were published. A total number of 246,160 tweets posted about the selected organisations were captured and used for analysis. The extracted dataset about the selected companies were separated according to the days they were published to uncover the rate at which customers posted tweets about their Mobile Network Operator (MNO). Section 4.2.1 presents a discussion of how the tweets were analysed daily, as this is the core element of temporal separation according to the SoMeDoA framework.

4.2.1 Tweets per Day

The analysis of tweets per day was carried out by analysing and studying the tweets to gain an insight on how frequent customers post tweets about their MNO. Figure 2 presents a tweet graph for July 3 2015, which has the highest number of published tweets of the days selected for analysis. The columns are positioned over a label representing the date and the time the tweets were published. The height of the column displays the number of tweets published from the chosen data set while the breadth indicates the date and the time of each tweet. A total number of 35,770 tweets were captured on Wednesday 3rd July 2015, displaying the highest rise on the graph (see figure 2). Subsequently, 35,752 tweets were captured on Tuesday, 2nd July 2015 (figure 3). Many of these tweets were about a popular musical artist who was performing in London. The day recorded with the least number of tweets is Saturday, 29th June 2015 (figure 4) - where a total of 32,450 tweets were captured. The number of tweets may be as a result of poor coverage quality as many tweets captured on this day emphasised problems with network quality. Some Three Mobile customers complained about their inability to make calls in certain locations. Poor coverage quality with respect to location was not investigated as that is not the objective of this study. The analysis also shows an interesting observation that occurred on the 1st of July 2015 (figure 5). O2 asked their customers to tweet about their overall customer experience. Many customers responded to this tweet by mostly tweeting about the problems they have experienced with the network. These problems included lack of support and long waiting time in the queue to speak with a customer service adviser. O2 responded to these tweets by sending an apology tweet later that day. Vodafone customers experienced a good day as there were little complaints about their services. The 3rd of July had the highest number of negative tweets on most of the investigated network providers. Majority of the negative tweets emphasised on poor customer service from T-Mobile and O2. Table 2 displays a table of senti-positive, senti-neutral and senti-negative scores of the MNOs that were studied. Senti-neutral has the highest scores while senti-negative has the lowest scores. From this table, we can understand that majority of the tweets had a neutral sentiment. The next section sheds more light on daily sentimental average of the published tweets.

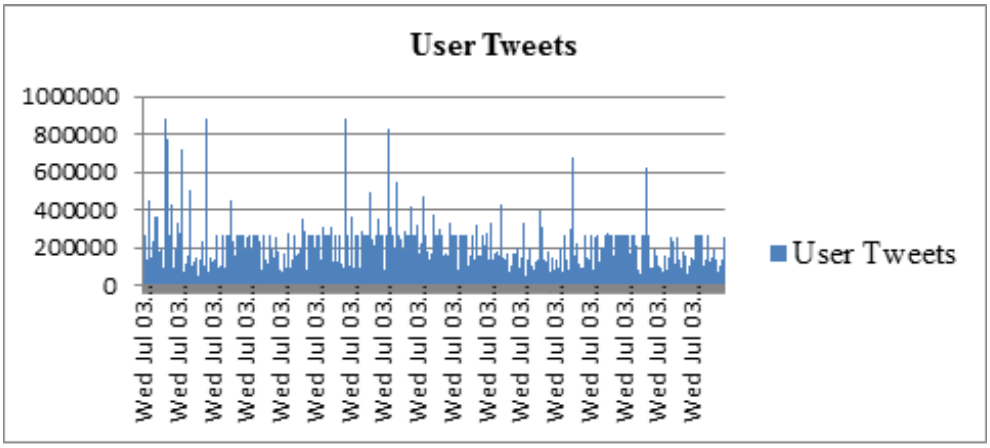

Figure 2. **Tweet graph for 3rd of July**

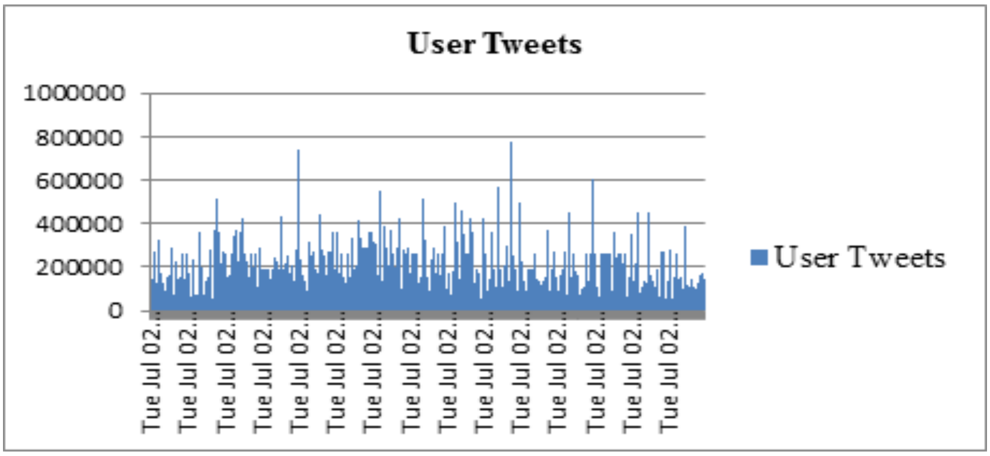

Figure 3 **Tweet graph for 2nd July**

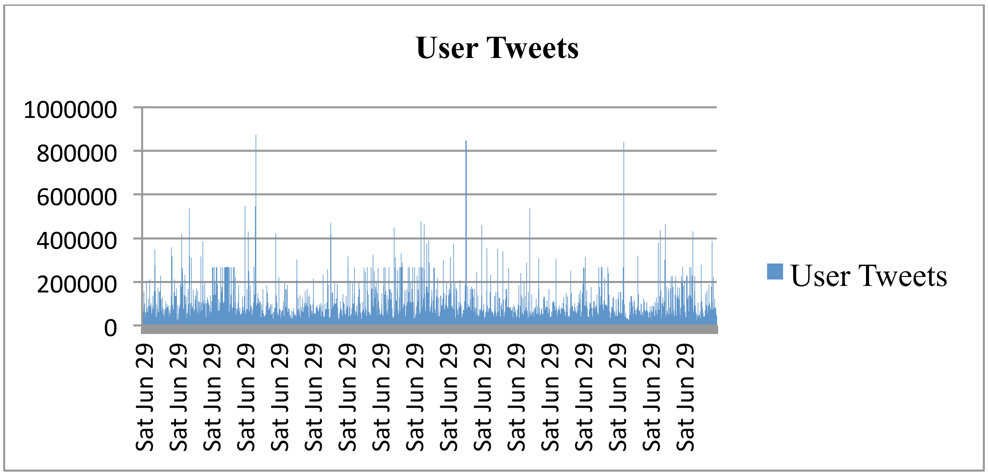

Figure 4. **Tweet graph for 29th June**

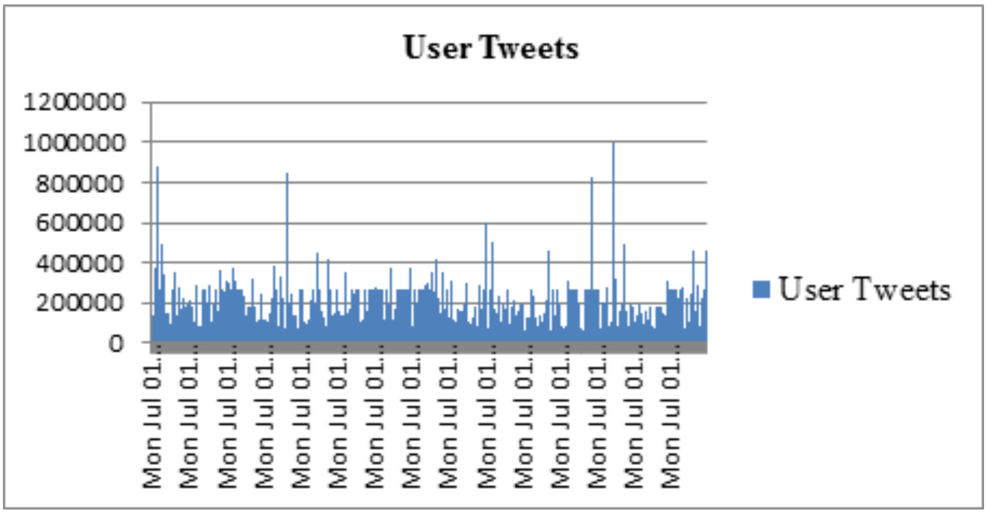

Figure 5. **Tweet graph for 1st of July**

Mobile Provider	Senti-Positive	Senti-Neutral	Senti-Negative
T-Mobile	31%	41%	28%
O2	29%	48%	23%
Three	31%	47%	22%
Virgin	31%	46%	26%
Vodafone	28%	50%	22%

Table 2. **Senti-scores for MNOs**

4.2.2 Sentiment Average Per Day

The sentiment average per day is the next phase for temporal separation according to the SoMeDoA framework. The senti-strength 7 tool developed by (Thelwall et al., 2010) and implemented in Brunel University's Tweetcatcher was used to report sentiment scores to each tweet. This tool simultaneously assigns positive and negative scores to words in a tweet with the idea that users can express both types of sentiments at the same time; for example, 'I love you, but I also hate you' (Kucuktunc et al., 2012). Positive sentiment scores range from +1 to +5, indicating not positive to extremely positive. Similarly, negative sentiment scores range from -1 to -5, indicating not negative to extremely negative (Kucuktunc et al., 2012). In order to get the final positive or negative sentiment score for a piece of text, the final positive or negative score is calculated by extracting the maximum score from all individual positive scores. The negative sentiment strength is similarly calculated. From the analysis, the majority of the tweets were assigned a neutral sentiment score (0). Slightly negative (+1/-2) and slightly positive (+2/-1) scores are also common. Table 3 displays the tabular description of the distribution of daily sentiment scores in percentage. Overall, there were more neutral sentiments (0). These sentiments were between 47% and 51%. Positive sentiments (+2/-1) were between 28% and 31% while negative sentiments (+1/-2) were between 21% and 25%. Figure 6 presents a graph of the daily sentiment analysis for the dataset. The colours green, blue and red represent positive, neutral and negative sentiment scores respectively. The daily sentiment analysis does not show the actual content of the tweets. Hence, to gain a deeper understanding of the contents of the tweets, temporal coding, which is the next phase after temporal separation was conducted. Temporal coding was carried out by using Nvivo10 to count word frequency on the tweets.

Timeslot	Senti-Positive	Senti-Neutral	Senti-Negative
27th June 2013	28%	50%	22%
28th June 2013	30%	66%	24%
29th June 2013	28%	51%	21%

30th June 2013	29%	47%	24%
1st July 2013	31%	48%	21%
2nd July 2013	30%	47%	23%
3rd July 3013	28%	47%	25%

Table 3. Distribution of daily sentiment scores

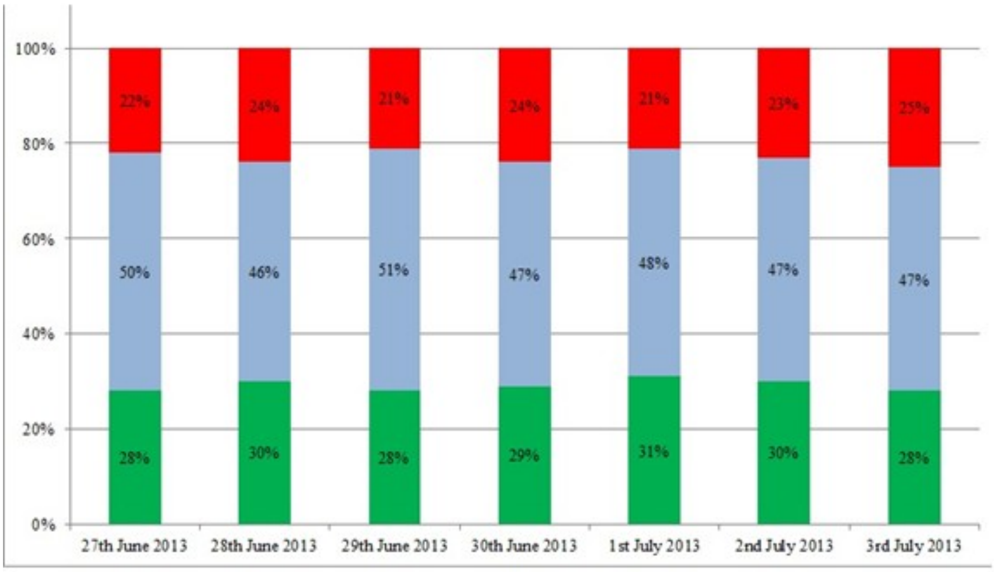

Figure 6. Daily senti-score

4.3 Temporal Coding

A number of researchers have debated the process of coding. Strauss and Corbin (1998) described the process of coding in forms of open coding, axial coding and selective coding. Open coding is the initial basic coding of the original data. Axial coding involves putting categories together into a hierarchy, and selective coding is the process of incorporating and refining categories to arrive at a theory (Strauss and Corbin, 1998). Nvivo10 was used to analyse the dataset for this study. Figure 7 presents a graphical representation of the process of importing and categorising tweets.

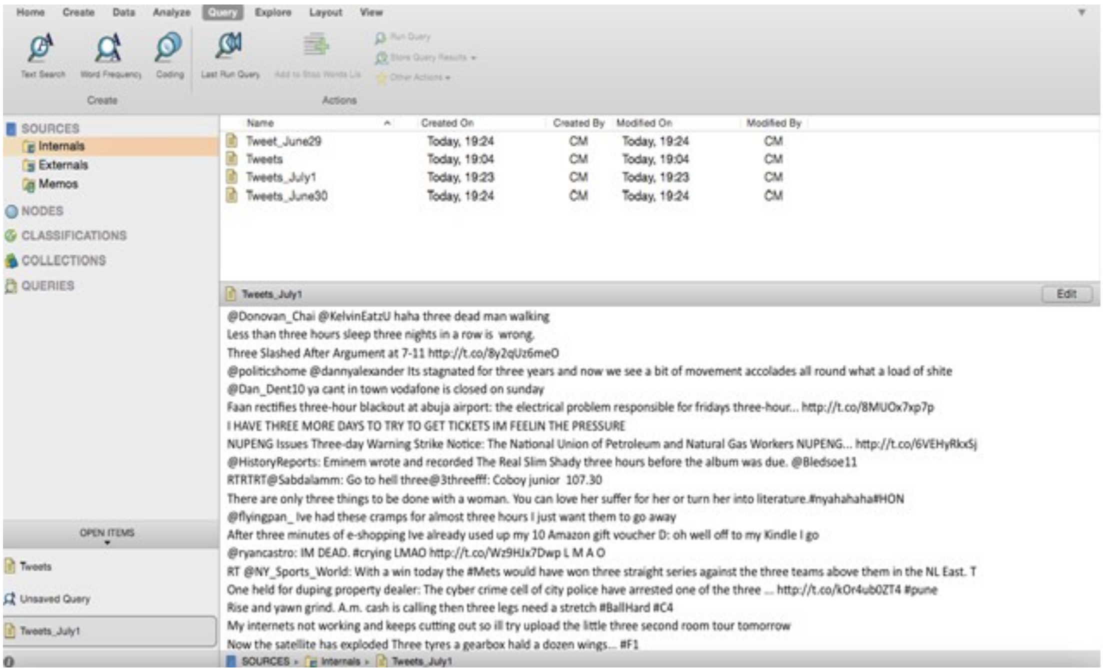

Figure 7. Importing and Categorsing Tweets using Nvivo10

4.3.1 Tweets per Word

The next step for carrying out temporal coding on the dataset is analysing tweets per word. The tweets captured for this study were scrutinised and interpreted by undergoing a coding process to achieve the best result. The SoMeDoA approach, which was adopted to analyse the tweets makes use of GTM coding approach (see section 3.1). The process was achieved by counting the word frequency of the tweets using Nvivo10. In the first round of Nvivo10 analysis, the most frequent words in the dataset include 'rt', 'direction', 'three', 'you', 'contest', 'my', 'virgin', and 'days' (see figure 8). From these list of words, only 'three' and 'virgin' are relevant to this study. Hence, tweets about 'three' and 'virgin' are reviewed. Interestingly, many of these tweets are not about Three mobile and Virgin as a service provider. Thus, they are not relevant to this study and they were separated from other tweets. The irrelevant 'three' and 'virgin' tweets were identified by carrying out a word search on Microsoft Excel and reading through the tweets. During this process, tweets about each mobile operator were saved in a separate file. Sentiment analysis was further carried out on the tweets about the selected MNOs to uncover the satisfaction level of customers with their MNO (see table 2). After separating the Twitter files according to each mobile operator, the files for each mobile operator were loaded into Nvivo10 and a word frequency count was conducted. The second round of the word frequency count using Nvivo10 revealed more words that are related to the topic and domain under study. These words include ‘digital’, ‘O2’, ‘direct’, ‘communication’, and ‘4G’. The bolder the word, the more frequent it is in the dataset (see figure 9). Based on the frequency of words in this analysis, the themes and subthemes, which determine the CSDs in this study, are derived. Themes in this context refer to possible words that denote satisfaction or dissatisfaction, and subthemes are words that are similar in meaning to themes. The derivation of CSDs from themes and subthemes are explained in the next section.

Figure 8. **First round of frequent words in tweets**

Figure 9. **Second Iteration of Frequent Words In Tweets**

4.4 Reporting Determinants with an Ontology-Based Concept Network

Computational ontologies (with associated semantic web technologies) can support the SoMeDoA framework in many ways. Firstly, through reasoning and inference techniques, ontologies restrict the modelling of conflicting or inconsistent information. The SoMeDoA framework with ontologies can ensure the validity of the information encoded. Secondly, ontologies are commonly deployed for the specification and clarification of concepts and relationships related to a given domain. The SoMeDoA framework has the same purpose but with a focus on social relationships and entities, hence domain ontologies describing social entities and relationships can be represented. Thirdly, ontologies together with inference mechanism enable information to be gained by deploying rules to infer new information. Inference mechanisms can be implemented over ontology-based social networks to uncover new relationships and concepts from those existing between social entities i.e. people, organisations, events and locations. Through important relationships and implied similarity, computational ontology enhances the modelling of codes and categories (from GTM analysis). As mentioned in the SoMeDoA approach (Table 1), GTM is used to analyse the textual content of Tweets. The first activity taken from GTM is open coding. Open coding is the process of reviewing every imported file, phrase and word. Each of the entities will be allowed a code (a Free Node in Nvivo10 terms) (see figure 10). The base codes will be reviewed and the codes to have, or appear to have the same meaning will be merged. Axial coding will then be applied to review the remaining nodes (Free Nodes) while the related nodes are grouped together under a new higher-level code. The process of axial coding will go through several iterations as ideas change and new relationships emerge. Glaser and Strauss (1971) referred to this process as 'constant comparison', which is a core feature of their proposed GTM method. This process is also similar to the loop of the Design Research stages, as described by von Alan et al. (2004) (see section 3.0). The axial coding content resulted in some categories and subcategories. The categories and subcategories are regarded as themes and subthemes in this study. These themes and subthemes include payment, bills, support, data, upgrade, annoying, appalling and bad experience. For example, a price category was created with associations to payment, bills, credit and extra charges. Figure 10 presents the process of storing and categorising datasets. Subsequently, this dataset was analysed and ontology was created using the protégé 4.3 Onto Graf (figure 11).

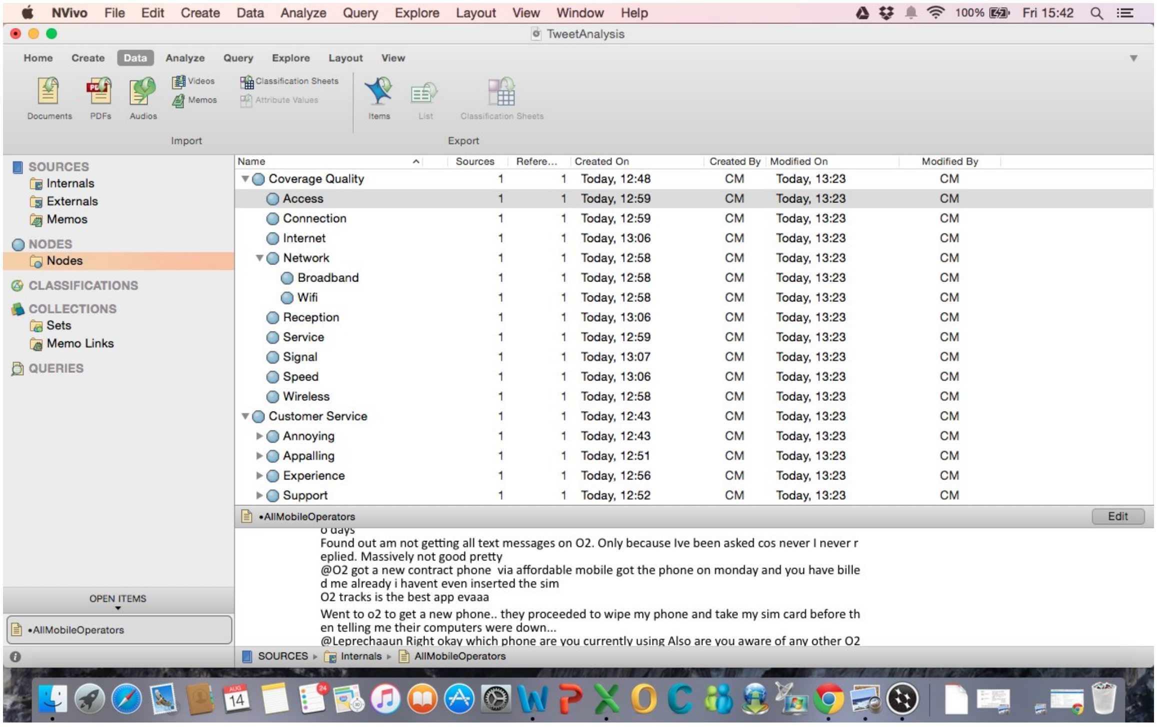

Figure 10. **Storing And categorising Tweets**

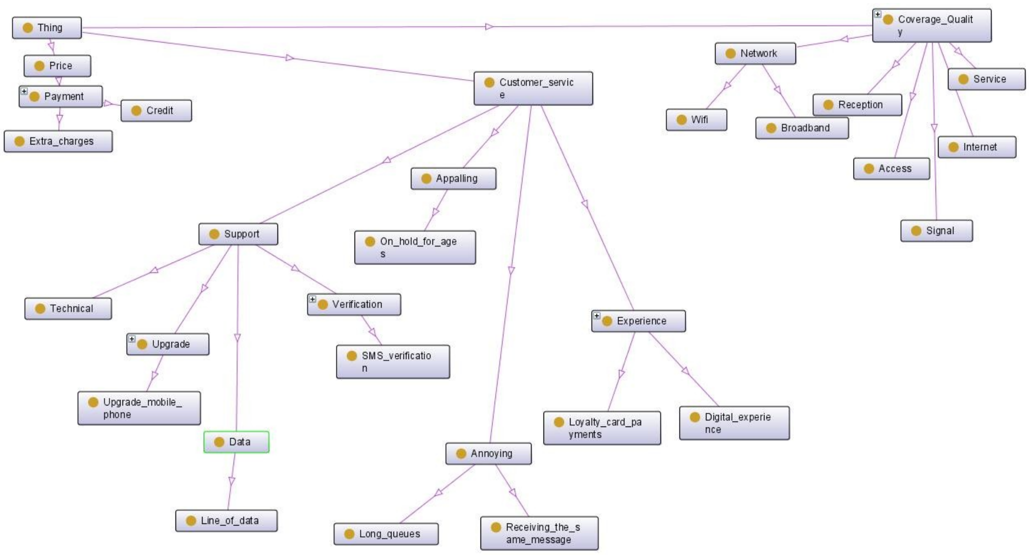

Figure 11. **CSD OntoGraph**

4.6 Sentimental Average per Word

Table 4 presents the main nodes that are classified as 'themes' in this analysis. The themes derived in this analysis make up the CSDs. Sentiment analysis was carried out on the CSDs to determine the number of positive and negative tweets that were published under each determinant. Table 4 presents a comprehensive view of the number of positive and negative tweets under each ‘theme’ and the average frequency of occurrence for each CSD. Price has the highest percentage of positive sentiment. The high percentage could be because customers who are on a contract with their MNO are already aware of the monthly price plan of the package they have chosen. The senti-negative percentage for Price is 42%. This percentile score is the lowest amongst the determinants, but it is a relatively high score. The high percentage could be because customers were charged when they did not expect to incur charges. From the sentiment analysis of each CSD, customer service and coverage quality seem to be of high importance because they both have a higher number of tweets than price. As seen in table 4, customer service has a positive percentage of 55%, and coverage quality has a positive percentage of 56%. These scores do not indicate that customers had a better coverage during the period of analysis. It could be because of the number of tweets published about each the determinants of customer satisfaction. A total of 21,742 tweets were published regarding customer service while a total of 19,055 tweets were published about coverage quality. From these published tweets, customer service had a total of 12,055 positive tweets; coverage quality had a total of 10,662 published tweets. Subsequently, customer service has a total of 9,687 negative tweets and coverage quality has a total of 8,393 negative tweets. In order to determine how reliable the SoMeDoA approach is in uncovering the determinants of customer satisfaction, an evaluation procedure is conducted. The aim of the evaluation procedure is to understand if the determinants of customer satisfaction derived using the SoMeDoA approach are factors that make customers satisfied or dissatisfied with their MNO. The evaluation procedure also seeks to uncover more determinants of customer satisfaction.

Name	#Senti-Pos.	#Senti-Neg.	Senti-Pos. (Percentage)	Senti-Neg (Percentage)	Senti-Pos Average	Senti-Neg Average
Customer Service	12055	9687	55%	45%	1.31616	1.43888
Coverage Quality	10662	8393	56%	44%	1.31617	1.46467
Price	9292	6716	58%	42%	1.336849	1.56566

Table 4. Senti-scores for CSDs

4.6 Evaluation

In line with the design science research methodology, this study has to be evaluated. The SoMeDoA approach is a novel approach for investigating the determinants of customer satisfaction in the mobile services industry, and it is important to validate the findings derived by using this approach. As displayed in figures 11 and 12, Customer services, Coverage Quality and Price were found to be the determinants of customer satisfaction. In order to validate the finding derived in this study, a set of interviews were conducted. The three basic approaches to conducting interviews include structured, semi-structured and unstructured (Oates, 2005). The structured interviews are based on planned, standardised and identical questions for every interviewee. Semi-structured interviews are conducted with a fairly open framework, which allows for focused, conversational, two-way communication. Unstructured interviews are not specifically limited to a set of questions to allow the conversation flow freely. In this study, the semi-structured interview approach was adopted. A random sample of four customers for each MNO used for this study was interviewed. A total of 20 customers were interviewed. Before commencing with the interviews, the interview questions were tested with three participants. These participants shared their thoughts on how to make the interview questions more focused to the research objective. The interview questions were re-written in regards to the thoughts shared by the participants. After reviewing the interview questions, two interviews were further conducted to test the new set of questions. Again, more thoughts were shared on how to make the questions better and more focused to the research objective. The interview questions were designed to validate the CSDs identified using the SoMeDoA approach; Customer service, Coverage quality and Price. The questions were asked in such a way that the participants could express their general views on the determinants of customer satisfaction. Overall, the interviewed participants emphasised on customer service and coverage quality to be their main determinants of customer satisfaction. When a participant was asked why they have been with their mobile service operator for so long, they responded 'They have a brilliant customer service, and they also have good network quality'. Another participant talked about their experience with the customer service department of their MNO. They highlighted that 'Customer service is very important as one can get upset if their problems are not resolved'. Apart from customer service and coverage quality, participants also emphasised the importance of price as a factor for customer satisfaction. One major finding of this factor is that most of the interviewed participants already knew the cost of the package they signed up with their mobile provider. However, a few participants complained about incurring unexpected charges. When a participant was asked if price is a major factor for them to be satisfied with their MNO, they responded by saying, ‘Price is a major issue for me with my mobile operator. I do not like when I am charged, and I do not know why I am charged. I chose my mobile operator because they offered a cheaper price than other competitors. I guess I made a mistake, I should have considered their reputation before choosing them’. Another customer also emphasised on reputation as one of the factors that make them satisfied with their mobile provider. When the asked ‘To the best of your knowledge which mobile operator stands out at providing the best network/coverage quality and what has the company done to make you feel that way?’ Their response was, ‘O2. My friend has been with them for 5 years. He always talks about their good customer service and network quality. He also praises them because of their reputation and their advertisements’. Value added service is another factor found to be a determinant of customer satisfaction. A Virgin customer highlighted that he is satisfied with his MNO because they have given him discounted prices and incentives (such as, Virgin broadband and TV). Although, majority of the interviewed participants emphases on customer service and coverage quality to be their major determinants of customer satisfaction, the interviews conducted also found reputation, and value added services to be part of the determinants of customer satisfaction in the mobile services industry.

5. Conclusion

The exploration of data from social media and its adequate utilisation is able to provide organisations with a better relationship with their customers as engaging in social media can help create a better understanding of customer needs. In addition, social media gives organisations the opportunity to respond promptly to customer needs. Social media has made it possible for customers to complain directly to organistions they operate with. For example, on twitter, a customer is able to use signs such as ‘@’ or ‘#’ with a chosen company name to pass a messge across to that company. This has made it easier for organisatons to contact individuals directly when the need arises. The dataset utilized in this study was captured from twitter using keywords specific to mobile services companies of interest. The SoMeDoA approach was adopted (Shirzad and Bell, 2013) to uncover customers’ feelings towards the MNO. A total of 246,160 tweets were captured and

CSDs were derived based on the analysis as discussed in section 4. The CSDs derived in this study are Customer service, Coverage quality, and Price. The findings for this study were evaluated using semi-structured interviews. During the interview sessions, a number of customers added that value added services and reputation also drive their satisfaction towards their MNO. Although, we were able to achieve the objective of this study using the SoMeDoA approach, a number of limitations for this study have been identified and possible ways for addressing the limitations are proposed. The main limitation in this study is that data was captured and analysed for one week. Analysing data for a longer period of time may bring about more interesting results. Also, comparing results for several weeks may showcase some more interesting CSDs. Also, capturing and integrating data from other social media platforms such as Facebook, and Instagram may uncover some more interesting results as some customers may actively engage in selected social media platforms. Analysing data from a single platform means that some customers' opinions are neglected. Analysing data from multiple social media platforms may create a competitive edge for existing companies and can also provide a platform to build a new company for customer satisfaction. Figure 12 presents the CSDs derived from applying the SoMeDoA approach in this study.

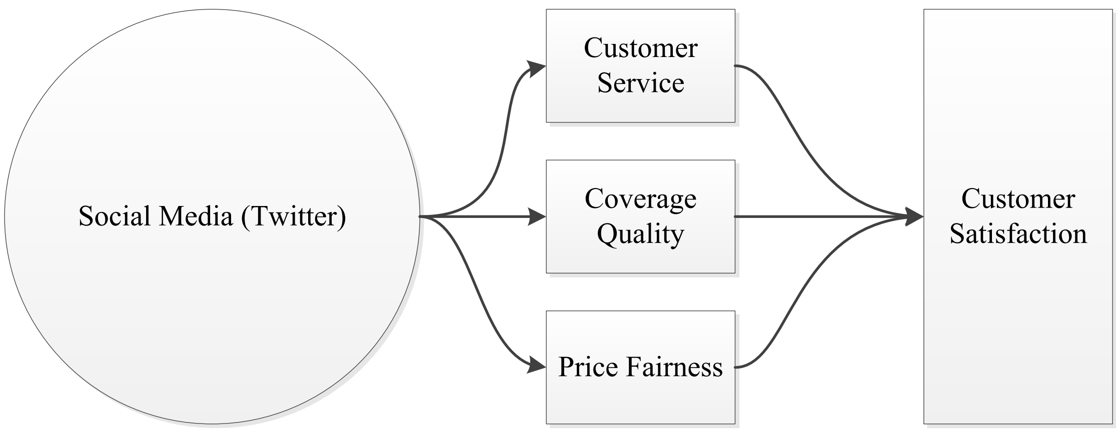

Figure 12. Customer Satisfaction Determinants

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